IJARSCT

ISSN (Online) 2581-9429

International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)

IJARSCT
Impact Factor: 6.252

Volume 2, Issue 9, June 2022

# Ameliorated Automated Facial Fracture Detection System using CNN

**Ramireddy Renusree[1], Ramireddy Sandhya[2], Somagattu Chandrika[3], Vemuleti Charitha[4], Dr. Murthy SVN[5]**

Students, Department of Computer Science and Engineering[1,2,3,4]

Faculty, Department of Computer Science and Engineering[5]

S J C Institute of Technology, Chickballapura, Karnataka, India

**Abstract:** *The fracture of the bone is common issue in human body occurs when the pressure is applied on bone or minor accident and also due to osteoporosis and bone cancer. Therefore the accurate diagnosis of bone fracture is an important aspects in medical field. In this work X-ray/CT images are used for the bone fracture analysis. The main aim of the this project is to develop an image processing based efficient system for a quick and accurate classification of bone fractures based on the information gained from the x-ray / CT images of the skull. X- ray/CT scan images of the fractured bone are collected from the hospital and processing techniques like pre-processing method, segmentation method, edge detection and feature extraction methods are adopted. The images are tested out by considering the image slice of single slice and also grouping the slices of the patients. The patients CT scan/X-ray image was classified if bone is fractured then if two following slices were categorized with a probability fracture higher than 0.99. The results of the patient x-ray images show that the model accuracy of the maxillofacial fractures is contains 80%. Even the radiologist's work is not replaced by the MFDS model system, it is useful only for the providing valuable assistive support, it reduces the human error in the medical field, preventing the harm for the patients by minimizing the diagnostic delays, and reducing the incongruous burden of hospitalization.*

**Keywords:** Convolution Neural Network; Maxillofacial Fractures; Computed Tomography Images; Radiography

## I. INTRODUCTION

Bones are the rigid organs in the human body shielding many key organs such as brain, heart, lungs and other internal organs. The human body has 206 bones with numerous shapes, size and structures. The huge bones are the femur bones, and the little bones are the auditory ossicles. Bone fracture is aordinary issue in human beings. Bone fractures can happen due to accident or any other case in which high pressure is put in on the bones. There are various types of bone breakage occurs are oblique, compound, comminuted, spiral, greenstick and transverse. There are various types of medical imaging tools are accessible to descry different types of malformation such as X-ray, Computed Tomography (CT), Magnetic Resonance Imaging (MRI), ultrasound etc. X-rays and CT are most regularly used in fracture recognition because it is the speedy and quite way for the doctors to study the bruise of bones and joints. Doctors generally uses x-ray images to decide whether a fracture exists, and the location of the fracture. The database is DICOM images. In modern hospitals, medical images are stockpile in the standard DICOM (Digital Imaging and Communications in Medicine) format which incorporate text into the images. Any strive to recover and display these images must go through PACS (Picture Archives and Communication System) hardware.

Deep learning, a branch of AI, has recently made significant progress in examining images with a following better delineation and explanation of compound data. In specific, different works deal with deep learning in orthopedic traumatology. However, the number of studies concerning deep learning on CT scans for fracture noticing is less. Moreover, building and training a neural architecture from beginning needs a large amount of data. Image classification networks are instructed on billions of data in the literature, using multiple servers running for several weeks. This plan of action is not practicable for most medical researchers. One method to get the better of this hurdle is to use the so-called transfer learning. This procedure comprise of acquiring the highly purified characteristics of convolutional neural networks ordered on millions of data and using them as ainitial point for a new model. For example, to confirm the enlarge of fracture detection on wrist radiographs, Kim and MacKinnon pivot on transfer learning from a deep convolutional neural network (CNNs), pre-trained on non- medical images. Using the inception V3 CNN [9], they obtained an area under the receiver operating characteristic curve (AUC-ROC) of 0.95 on the test dataset. This result shows that a CNN pre-trained on non-medical images can be used for medical radiographs ultimately. One more study was done by Chung et al., based on a CNN to detect and differentiate proximal humerus fractures using plain anteroposterior shoulder radiographs. The deep neural network manifested a matched performance to that of shoulder-specialized orthopedic surgeons, but better than that of the general physicians and the non-shoulder trained orthopedic surgeons. This result denotes the likelihood to diagnose fractures correctly by using plain radiographs naturally. One more study in this field was done by Tomita et al., where they concentrated on determining osteoporotic vertebral fractures on CT exams. Their system comprise of two blocks:

1. A CNN to extract radiological features from CTs; and
2. A recurrent neural network (RNN) module to aggregate the earlier extracted elements for the final diagnosis. The presentation of the proposed system complement the ability of radiologist practitioners. Thus, the system could be ability of radiologist practitioners.

## II. LITERATURE SURVEY

1. D.B.McGrigor&late Major W.Campbell were explained the Radiology of war injuries, wounds of face and jaw Classification of injuries, radiological reports are done upon the fractures of the face and jaw.The features are demanded in a radiological report upon only injuries to the face and jaw is stressed.
2. Ralph N.Akamine.Diagnosis of the traumatic injuries of the face and jaw When associated injuries are suspected, medical consultation should be sought before proceeding with definitive treatment. Greater complexity emphasis is laid on the signs and symptoms of maxillofacial injuries.
3. A S Grove. New techniques for the evaluation of orbital trauma in diagnostics By using conventional roentgenograms with linear or hypocycloidal tomography the fractures are evaluated. Damage to the paranasal sinuses and the nasolacrimal system has considered as a possible relevance of trauma to the orbit.
4. M.J.C.Davdidson,B.D.Daly,J.L.Russell.The use of computed tomography in the management of facial trauma byBritish oral and maxillofacial surgeons The access to CT Scanners and the value ofthe reports in the management of patients was rated as satisfactory by 75% of respondents & similar % reported that CT service was becoming increasingly available to their units. No advantage in CT imaging over plain radiography.
5. P W Cooper.High-resolution CT scanning of facial trauma Surgical findings of extent of fracturingcorrelate better with resolution scanning than with plain films and conventional tomography. Due to high resolution the CTscanner requires extra time.
6. Aim to Moilanen.Primary radiographic diagnosis of fractures in the mandible To determine the reliability of primary radiography in evaluation of fractures in the mandible. Fractures in the dento – alveolar presented repeated difficulties in initial radiography.
7. RH Haug,J Oral.Cranial fractures associated with facial fractures: A review of mechanism, type and severity of injury A review was undertaken to identify the population characteristics of patients with both facial and cranial fractures. He presence of cranial fractures did not play a role in the development of complications associated with facial fractures.

## III. PROPOSED SYSTEM

The CT images of the cranial is obtained according to the standard clinical CT acquisition protocol for patient and preprocessing of the acquired images to construct the data set. The pixels are representing the labeled as lesions of the fracture. By using bilinear interpolation the axial 2D slices are researched to uniform the axial dimensions of 512 ×512 pixels. We are using CNN (convolution neural network) to predict SKULL fracture. To train CNN author is using CT SCAN images and this images are not available in huge numbers so author is applying Transfer Learning mechanism with pre trained RESNET50 as this algorithm already trained on non-medical images and will have massive amount of


DOI: 10.48175/IJARSCT-5314

features so we can include fewer CT SCAN images in this RESNET model to trained our own Fracture detection model. By adding transfer learning concept we can increase prediction accuracy and avoid model over-fitting problem which may rises due to less amount of dataset images. To implement this project we have designed following modules

1. Upload Skull-Fracture Dataset: using this module we will upload SKULL fracture CT-SCAN images to application
2. Preprocess Dataset: using this module we will read all CT-SCAN images and then resize to equal size and then normalize all pixel values and then split dataset into train and test where application used 80% images dataset from training and 20% dataset for testing
3. Train Resnet50 CNN Model: using this module we will train RESNET50 transfer learning with CNN by using above train and test data and then build a prediction model
4. Accuracy Graph: using this module we will plot RESNET50 transfer learning CNN accuracy and loss graph
5. Predict Fracture from Test Image: By using this type of module,it is easy to upload the test image and also then CNN will predict weather image is FRACTURE or NON_FRACTURE.

## IV. OUTPUT OF THE PROJECT

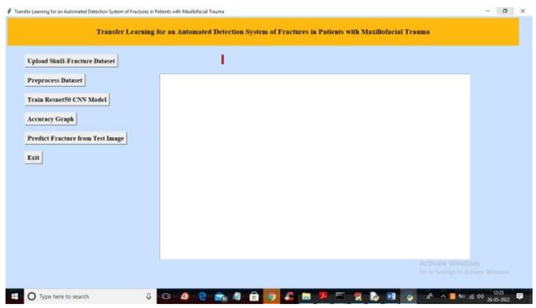


Figure1: Home screen with dataset upload

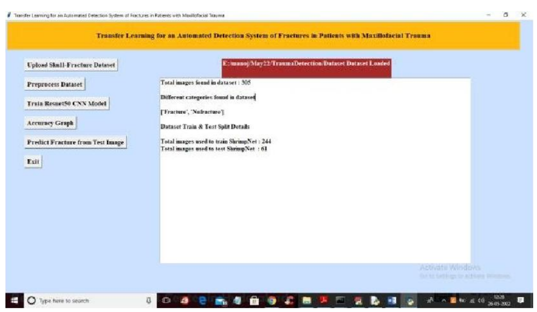


Figure 2: In above screen dataset contains total 305 images and application using 244 images for the training and 61 images for the testing

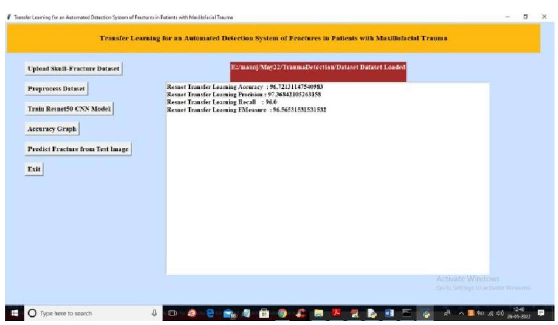


Figure 3: In above screen with RESNET50 transfer learning CNN we got 96% accuracy

ISSN (Online) 2581-9429
IJARSCT
International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)
Impact Factor: 6.252
Volume 2, Issue 9, June 2022

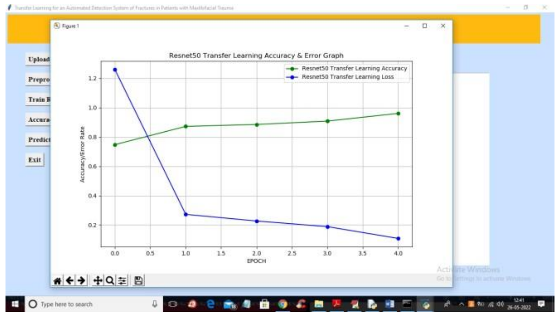


Figure 4: In above graph x-axis shows the training EPOCH and y-axis shows the accuracy and also the loss values and in above graph green line shows accuracy and blue line represents LOSS

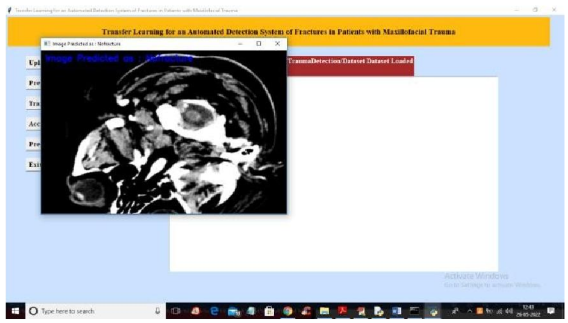


Figure 5: In above screen in blue colour text we can see image predicted as ‘No Fracture’

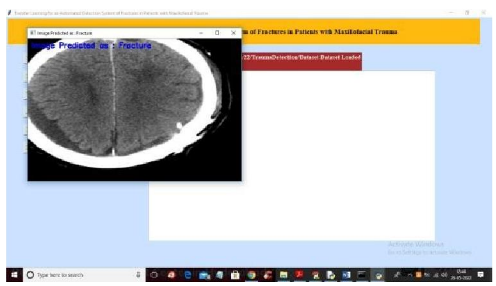

Figure 6: In above image Fracture is predicted and similarly you can upload and test other images

## V. CONCLUSION

The detection of the bone fracture by using X- ray/CT images on the basis of a computer based analysis has been exposed in this work. The preprocessing help to remove the noise and also edge detected by using sobel edge detector. The area of the fracture is calculated after the segmentation. We are applying Transfer Learning mechanism with Pretrained RESNET50 as this algorithm already trained on non-medical images and will have massive amount of features so we included CT SCAN images in this RESNET model to trained our own Fracture detection model. By adding transfer learning concept we can increase prediction accuracy and avoid model over-fitting problem which may rises due to less amount of dataset images.

## REFERENCES

**[1].** Kalmet, P.H.S.; Sanduleanu, S.; Primakov, S.; Wu, G.; Jochems, A.; Refaee, T.; Ibrahim, A.; Hulst, L.V.; Lambin, P.; Poeze, M. Deep learning in fracture detection: A narrative review. Acta Orthop. 2020, 91, 215–220. [CrossRef]

**[2].** Esteva, A.; Kuprel, B.; Novoa, R.A.; Ko, J.; Swetter, S.M.; Blau, H.M.; Thrun, S. Dermatologist-level classification of skin cancer with deep neural networks. Nature 2017, 542, 115–118. [CrossRef]

**[3].** Gulshan, V.; Peng, L.; Coram, M.; Stumpe, M.C.; Wu, D.; Narayanaswamy, A.; Venugopalan, S.; Widner, K.; Madams, T.; Cuadros, J.; et al. Development and Validation of a Deep Learning Algorithm for Detection of Diabetic Retinopathy in Retinal Fundus Photographs. JAMA 2016, 316, 2402–2410. [CrossRef]

**[4].** Lee, J.-G.; Jun, S.; Cho, Y.-W.; Lee, H.; Kim, G.B.; Seo, J.B.; Kim, N. Deep Learning in Medical Imaging: General Overview. Korean J. Radiol. 2017, 18, 570–584. [CrossRef] [PubMed]

**[5].** Olczak, J.; Fahlberg, N.; Maki, A.; Razavian, A.S.; Jilert, A.; Stark, A.; Sköldenberg, O.; Gordon, M. Artificial intelligence for analyzing orthopedic trauma radiographs: Deep learning algorithms—are they on par with humans for diagnosing fractures? Acta Orthop. 2017, 88, 581–586. [CrossRef] [PubMed]

**[6].** Tang, A.; Tam, R.; Cadrin-Chênevert, A.; Guest, W.; Chong, J.; Barfett, J.; Chepelev, L.; Cairns, R.; Mitchell, J.R.; Cicero, M.D.; et al. Canadian Association of Radiologists White Paper on Artificial Intelligence in Radiology. Can. Assoc. Radiol. J. 2018, 69, 120–135. [CrossRef] [PubMed]

**[7].** Szegedy, C.; Liu, W.; Jia, Y.; Sermanet, P.; Reed, S.; Anguelov, D.; Erhan, D.; Vanhoucke, V.; Rabinovich, A. Going Deeper with Convolutions. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Boston, MA, USA, 7–12 June 2015; pp. 1–9.

**[8].** Kim, H.D.; MacKinnon, T. Artificial intelligence in fracture detection: Transfer learning from deep convolutional neu-ral networks. Clin. Radiol. 2018, 73, 439–445. [CrossRef] [PubMed]

**[9].** Szegedy, C.; Vanhoucke, V.; Ioffe, S.; Shlens, J.; Wojna, Z. Rethinking the Inception Architecture for Computer Vision. In Proceedings of the 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR) 2016, Las Vegas, NV, USA, 27–30 June 2016.

**[10].** Chung, S.W.; Han, S.S.; Lee, J.W.; Oh, K.- S.; Kim, N.R.; Yoon, J.P.; Kim, J.Y.; Moon, S.H.; Kwon, J.; Lee, H.-J.; et al. Automated detection and classification of the proximal humerus fracture by using deep learning algorithm. Acta Orthop. 2018, 89, 468–473. [CrossRef]

**[11].** Tomita, N.; Cheung, Y.Y.; Hassanpour, S. Deep neural networks for automatic detection of osteopo-rotic vertebral fractures on CT scans. Comput. Biol. Med. 2018, 98, 8–15. [CrossRef]

**[12].** Heo, M.-S.; Kim, J.-E.; Hwang, J.-J.; Han, S.-S.; Kim, J.-S.; Yi, W.-J.; Park, I.-W. Artificial intelligence in oral and maxillofacial radiology: What is currently possible? Dentomaxillofacial Radiol. 2021, 50, 20200375. [CrossRef]

**[13].** Hung, K.; Montalvao, C.; Tanaka, R.; Kawai, T.; Bornstein, M.M. The use and performance of artificial intelligence applications in dental and maxillofacial radiology: A systematic review. Dentomaxillofacial Radiol. 2020, 49, 20190107. [CrossRef] [PubMed]

**[14].** Litjens, G.; Kooi, T.; Bejnordi, B.E.; Setio, A.A.A.; Ciompi, F.; Ghafoorian, M.; van der Laak, J.A.; van Ginneken, B.; Sánchez, C.I. A survey on deep learning in medical image analysis. Med. Image Anal. 2017, 42, 60–88. [CrossRef] [PubMed]

**[15].** Nagi, R.; Aravinda, K.; Rakesh, N.; Gupta, R.; Pal, A.; Mann, A.K. Clinical applications and performance of intelligent systems in dental and maxillofacial radiology: A review. Imaging Sci. Dent. 2020, 50, 81–92. [CrossRef]

**[16].** Python.Available online: https://www.python.org/ (accessed on 24 June 2021).

**[17].** PyTorch Available online: https://pytorch.org/ (accessed on 3 July 2020).

**[18].** Fastai. Available online: https://docs.fast.ai/ (accessed on 3 February 2021).

**[19].** Scikit-Learn. Available online: https://scikit-learn.org/stable/ (accessed on 6 July 2020).

**[20].** Pydicom. Available online: https://pydicom.github.io/ (accessed on 8 July 2020).

**[21].** He, K.; Zhang, X.; Ren, S.; Sun, J. Deep residual learning for image recognition. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Las Vegas, NV, USA, 26 June–1 July 2016; pp. 770–778.

**[22].** Xie, S.; Girshick, R.; Dollar, P.; Tu, Z.; He, K. Aggregated Residual Transformations for Deep Neural Networks. In Proceedings of the 2017 IEEE Conference on Computer Vision and Pattern Recognition, Honolulu, HI, USA, 21–26 July 2017; pp. 1492–1500.

**[23].** Huang, G.; Liu, Z.; van der Maaten, L.; Weinberger, K.Q. Densely connected convolutional networks. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Honolulu, HI, USA, 22–25 July 2017; pp. 4700–4708.

**[24].** Russakovsky, O.; Deng, J.; Su, H.; Krause, J.; Satheesh, S.; Ma, S.; Huang, Z.; Karpathy, A.; Khosla, A.; Bernstein, M.; et al. ImageNet Large Scale Visual Recognition Challenge. Int. J. Comput. Vis. 2015, 115, 211–252. [CrossRef]

**[25].** Raschka, S. Model evaluation, model selection, and algorithm selection in machine learning. arXiv 2018, arXiv:1811.12808.

**[26].** Bergstra, J.; Bengio, Y. Random search for hyper-parameter optimization. J. Mach. Learn. Res. 2012, 13, 281–305.

**[27].** Learning Rate Finder. Available online: https://fastai1.fast.ai/callbacks.lr_finder.html (accessed on 3 February 2021).

**[28].** Howard, J.; Gugger, S. Fastai: A Layered API for Deep Learning. Information 2020, 11, 108. [CrossRef]

**[29].** Hanley, J.A.; McNeil, B.J. The meaning and use of the area under a receiver operating characteristic (ROC) curve. Radiology 1982, 143, 29–36. [CrossRef]

**[30].** Nicholls, A. Confidence limits, error bars and method comparison in molecular modeling. Part 1: The calculation of confidence intervals. J. Comput. Mol. Des. 2014, 28, 887–918. [CrossRef]